Image Segmentation and Compression using Neural Networks

Constantino Carlos Reyes-Aldasoro, Ana Laura Aldeco
Departamento de Sistemas Digitales
Instituto Tecnológico Autónomo de México
Río Hondo No. 1, Tizapán San Angel, 01000 México D.F.
creyes@itam.mx, al51578@alumnos.itam.mx

ABSTRACT

Kohonen [1] has developed an algorithm with self-organising properties for a network of adaptive elements. These elements receive an input signal and the signal representations are automatically mapped onto a set of output responses so that these responses acquire the same topological order as the input signal. Images can be used as input signals and the networks can adjust to extract certain topological features. Image segmentation can be performed satisfactorily. By empirical knowledge, it can be supposed that as the number of neurones increases, so does the quality of the segmentation. This paper concentrates on the relationship between the quality of segmentation and the number of neurones that constitute a Kohonen Neural Network. Several experiments were conducted and the Euclidean distance between adjacent neurones measured the quality of the segmentation, which tended to maintain constant after a certain optimum level. The amount of information of the original set of images was compared with the information of the segmented structure and results were presented. Compression rates higher than 250:1 were obtained.

Keywords: Neural Networks, Self-Organising Maps, Image Segmentation.

1. Introduction

Artificial Neural Networks are software or hardware systems that try to simulate a similar structure to the one that is believed the human brain has. Most neural networks in the brain, especially in the cortex, are formed by two-dimensional layers of cellular modules that are densely interconnected between them. This area of the brain is organised into several sensory modalities such as speech or hearing. The response signals of these areas are obtained in the same topographical order on the cortex in which they were received at the sensory organs.

The theoretical investigations in the self-organising maps (SOMs) [1] were motivated by the possibility that the representation of the knowledge in a particular category of things in general might assume the form of a feature map that is geometrically organised over a part of the brain. In this neural model, each neurone or node is densely interconnected with the rest of the neurones. The temporal status of a neurone, as well as the input signal, is represented by its topological position x, y, z.

The interconnection of neurones is considered as a lateral coupling. The function that defines the coupling has two different actions: excitatory and inhibitory. The excitatory interaction exists in a region defined by a short range up to a certain radius with the neurone as a centre, and the inhibitory region surrounds the excitatory area up to a bigger radius. Outside the inhibitory range, a weaker, and much bigger excitatory zone exists. The intensity of the action decreases as the distance from the neurone increases. A cluster or bubble, called the neighbourhood, around one particular node of the network is formed because of the lateral coupling around a given cell.

The primary input received by the network determines a "winner" neurone. Around this winner neurone, excitatory and inhibitory regions will form. The winner node will adapt to the input signal and then the neurones that lie within excitatory and inhibitory regions will adapt themselves accordingly. This process of adaptation will continue for a number of iterations until a certain degree of adaptation is reached. When the input is an image, certain features can be extracted from the final adaptation of the neurones.

The remaining of the document is organised as follows: the next section describes the implementation of the algorithm. Section 3 deals with the experiments over medical images, in section 4 a definition of the quality in terms of the number of neurones is presented, section 5 discusses the compression rate of the algorithm. Finally, conclusions are presented.

2. Implementation of the Kohonen Algorithm

The Self-Organising algorithm proposed by Kohonen [1] follows two basic equations: matching and finding the winner neurone determined by the minimum Euclidean distance to the input (1) and the update of the position of neurones inside the cluster (2).

$$\|x(t)-m_c(t)\| = \min_i \|x(t)-m_i(t)\| \qquad (1)$$

$$m_i(t+1) = m_i(t) + a(t)\left[x(t)-m_i(t)\right] \quad \mathrm{i} \in \mathrm{N_c} \quad (2)$$

$$m_i(t+1) = m_i(t) \qquad \mathrm{i} \notin \mathrm{N_c}$$

Where, for time *t*, and a network with *n* neurones:

- x is the input
- $\mathrm{N_c}$ is the neighbourhood of the winner, $1< \mathrm{N_c} <n$
- α is the gain sequence $0<\alpha<1$
- m_i is any node, $1<i<n$, and
- m_c is the winner,

It should be noted from equation (2) that the inhibitory region is not being considered and the intensity of the action inside the excitatory region was considered constant. The original "Mexican Hat" function was reduced to a gate function with satisfactory results (see Figure 1).

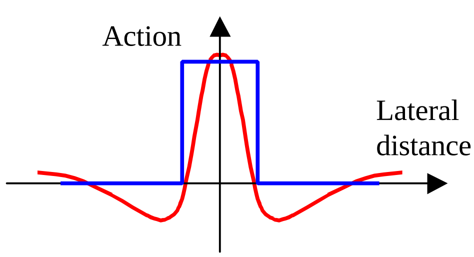


Figure 1 Lateral degree of interaction: Mexican Hat and Step Functions

Figure 2 describes graphically the Self-Organising algorithm. First, an input signal *x*, is received and the network determines a "winner" neurone by calculating the Euclidean distances with equation 1. The updating process of equation 2 is a variation of the topological location of the neurone, proportional to the Euclidean distance from the winner node to the input. The gain sequence α is a value between 0 and 1 that reduces with time. In Figure 2.a only the winner neurone adapts to the input signal and in Figure 2.b other neurones that lie within the neighbourhood of the winner adapt their topological co-ordinates. Neurones outside the neighbourhood remain unaltered. This process is reiterated until certain criterion is satisfied.

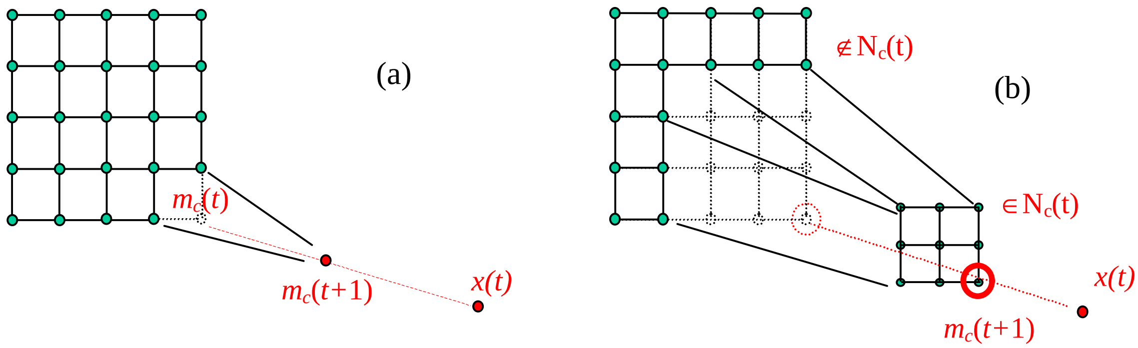


Figure 2 Graphical description of Self-Organising process

Kohonen [1] stated that the neighbourhood should be shrinking in time and α is a linearly decreasing function and the process stops when α=0. This behaviour allows a fast and coarse adaptation at the beginning of the process and a fine and slow adaptation at the end. Figure 3 shows an *n*-64 network (8 by 8) adapted to a square input region after 4000 iterations.

The initial values of the neighbourhood and the gain sequences and their variation with time are studied in [2].

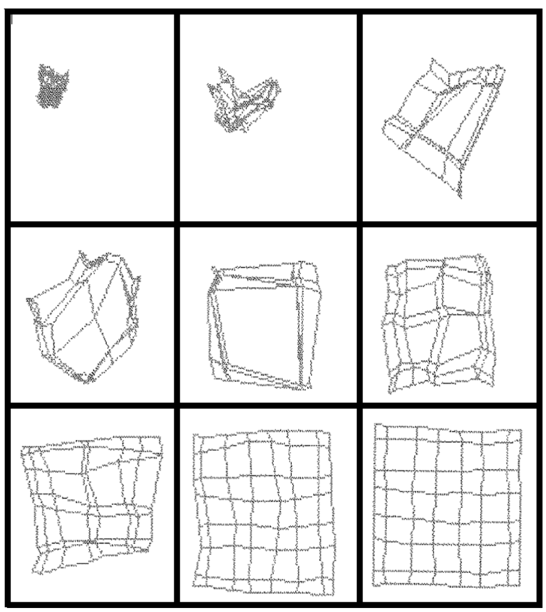


Figure 3. Adaptation of an 8*8 network to square input region.

3. *Experiments over medical images*

Medical Images have received considerable attention in several areas, being segmentation one of the most interesting ones [3]. The SOM algorithm can be related with medical image segmentation in the following way. The input signal received bye de SOM in figure 3 was a simple square region with equal probability for every position. If an image is to be used as input signal for a self-organising algorithm, a probability and a weight can be assigned to each pixel of the image.

Figure 4 shows a Magnetic Resonance (MR) image of a human head. This image can be converted to a two dimensional matrix where for each *x, y* position, a *z* value is assigned according to the grey level intensity of the current pixel.

This transformation allows the image to be used as input for a SOM. As the map receives the input, a winner is selected and then neighbourhood is updated to the image. This process can present interesting segmentation results of different structures of the image.

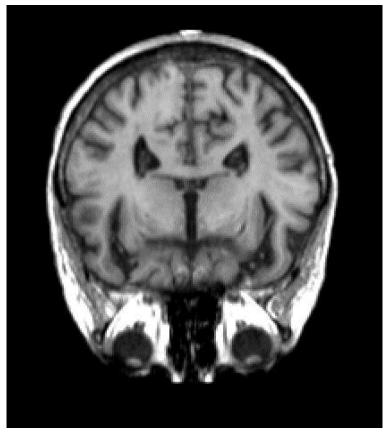


Figure 4 Human head Magnetic Resonance Image

As an example of segmentation, The image in figure 4 is pre-segmented by grey level and then an annular SOM with 80 neurones is used to segment the surface of the image. The result is presented in Figure 5.

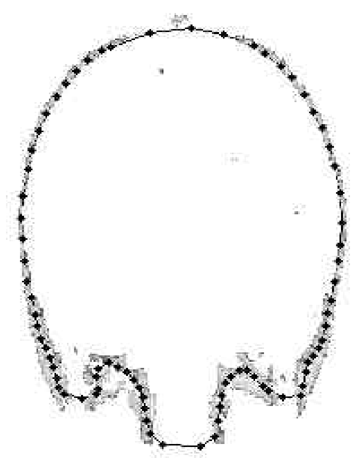


Figure 5 Segmentation of Magnetic Resonance image of figure 4.

It can be noted, that the number of neurones play a critical role in the segmentation process, and intuitively, as the number of neurones increases, the distance between them is reduced and therefore, the quality of the segmentation is also increased.

In [4] a MR images database of a human head is used to extract the border of the images, i.e. the shape of the head. In figure 6 the segmentation of 54 slices of a human head MR images is shown, for each slice, 58 neurones are used in the segmentation.

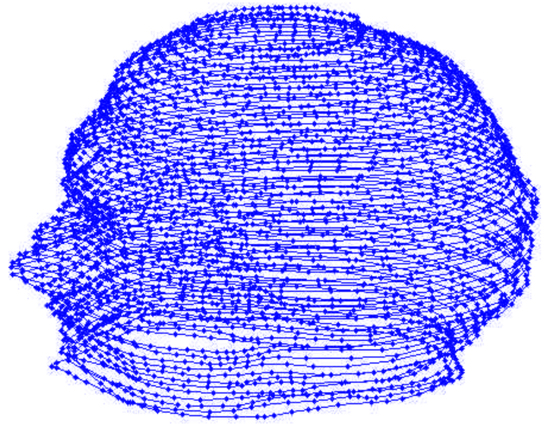


Figure 6 Segmentation of MR images of a human head

If the previous points are used to reconstruct the surface of the head, several problems arise. The algorithm presented in [5] is used to obtain the surface defined by the 3D collection of points depicted in figure 6. Along the surface, several "holes" are observed due to the lack of information in those specific positions. This lack of information is caused by the absence of a neurone in a critical x, y, z position that could have been avoided if more neurones would have been used in the segmentation.

Figure 7. Reconstruction of surface defined by the points in figure 6 shown as shaded image

It is obvious that adding neurones to the SOM will increase the computational complexity to the process defined by equations (1) and (2), therefore the number of neurones should not be increased at will. Indeed, the question arises, is there a limit in the quality of the segmentation as the number of neurones is increased?

The next section studies the segmentation quality, depending on the number of neurones.

4. Number of neurones and quality definition

The algorithm of the SOM that was presented in section 2 depends on a series of neurones that will self adapt to a certain input signal. As the neurones adapt to a signal, so does the Euclidean distance between the neurones. This distance can define the quality of the final segmentation as it can be seen on figure 8. The figure presents the final state of 4 SOMs with different number of neurones; 10, 20, 40 and 80. It can be observed that as the number of neurones increases, the shape defined by the neurones resembles better the shape of the human head as presented in the MR image of figure 4.

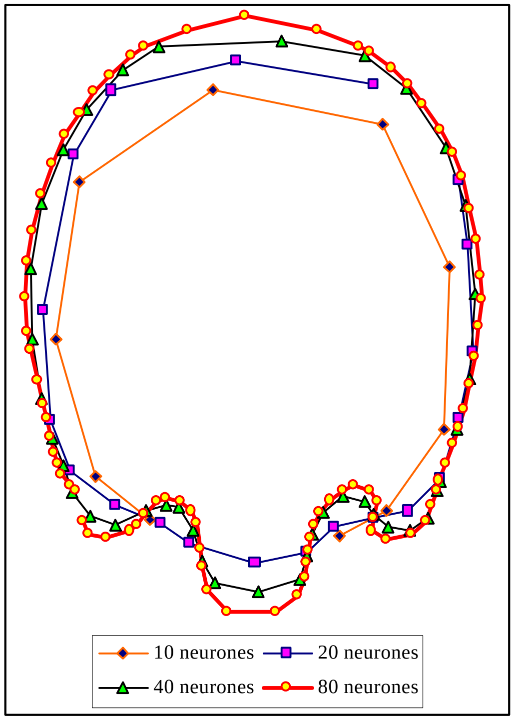


Figure 8 Segmentation obtained by SOM with different number of neurones

The SOM with 80 neurones is evidently better than the one with 10, but the difference between 80 and 40 neurones is not so clear, therefore, an analytic definition of the quality should be used. As the network adaptation is closer to the input signal, and the number of neurones increases, the distance between neurones will decrease. This distance between adjacent neurones will be used as a quality parameter following:

$$\bar{d}_{\max}^{adj} = \max_i \left\| m_i(t) - m_{i+1}(t) \right\| \qquad (3)$$

Three different MR images were used as input signals and equation (3) was applied to the segmentations obtained with SOMs of different number of neurones. The experiment was repeated numerous times to obtain an average measurement for each image. For all the experiments the parameters; Iterations = 15000, $\alpha(0) = 0.2$, and $N_c = 0.4\ n$ were constant.

In the three cases, the maximum distance between adjacent neurones tended to decrease asymptotically as the number of neurones increased. The final number of neurones will depend on the particular image, but in all cases a limit value seemed to be obtained closer to 300 neurones, after this region, the number of neurones make no difference in the quality of the segmentation.

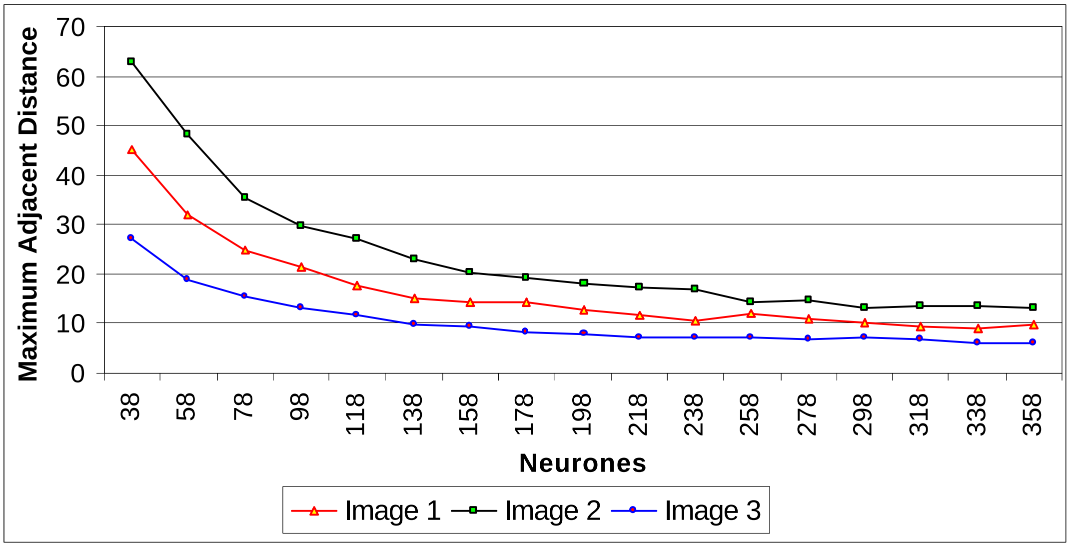
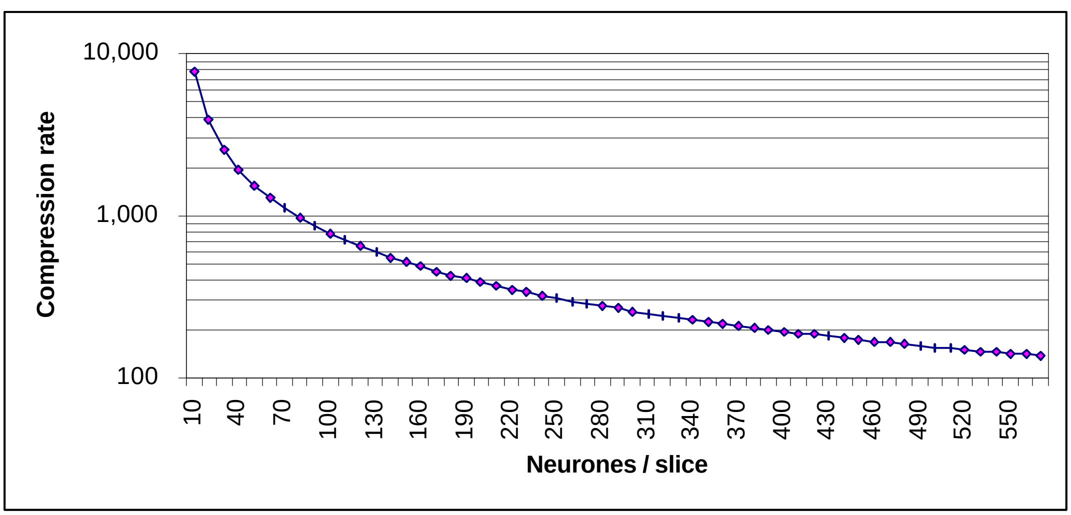


Figure 9 Maximum distance between adjacent neurones

5. Compression Rate

The process of segmentation of a certain structure of the image, as the external shape of a human head in the past examples, implies a loss of information. The segmentation deliberately looses the information that corresponds to all the internal structures such as the brain, cerebellum, and ventricles and retains the position of the external contour. Nevertheless, through this process, the amount of information corresponding to the *x, y, z* positions of the neurones is considerably less than the original image.



The images consist of 512*512 pixels, each with 256 levels of grey, or 8 bits/pixel. Each slice of the MR implies therefore:

I_{image} = 512*512*8 = 2,097,152 [bits].

And the whole set of 54 MR images of a human head:

$$I_{head} = 512*512*8*54 = 113,246,208 \text{ [bits]}.$$

The resulting SOM will require in turn the *x, y, z* position for each neurone or 9 * 3 = 27 bits/neurone. Figure 6 has 54 SOMs, each with 58 neurones, 84,564 [bits], a compression rate closer to 1340:1. Evidently, the original set of images contain the *whole* head, but at this rate, other 1300 similar structures could be segmented and treated as a single database with the same amount of information as the original set of images. Figure 10 presents the relationship of the compression rate and the number of neurones. If a number of 310 neurones is considered as the optimum for the adjacent distance, the compression rate would be 250:1.

6. Conclusions

The Kohonen Self-Organising Algorithm was programmed to use medical images as input signals. The use of an annular Self-Organising Map allowed segmenting the external shape of a human head out of database of Magnetic Resonance images. Through this process of segmentation, the information describing certain structures of the image is discarded thus compressing the information required to describe the segmented structure. Numerous experiments were conducted over different images to determine the quality of the segmentation measured as the maximum distance between adjacent neurones of a SOM. These experiments showed that as the number of neurones increased, the distance decreased up to a certain level where distance tend to remain constant. An optimum number of neurones will depend on the particular type of image to be processed. As the number of neurones increase, so does the amount of information comprised by the positions of the SOM, and therefore, the compression rate decreases. The final compression rate will be determined by the particular complexity image to be segmented its and the quality desired, but even with 310 neurones, the compression rate would be 250:1. The results encourage the use of SOM for image segmentation.

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